INTECH
open science | open minds

OPEN ACCESS
ARTICLE

International Journal of Engineering Business Management
Special Issue on Innovations in Fashion Industry

Merchandise and Replenishment Planning Optimisation for Fashion Retail

Regular Paper

Raffaele Iannone[1,*], Angela Ingenito[1], Giada Martino[1], Salvatore Miranda[1], Claudia Pepe[1] and Stefano Riemma[1]

1 Dept. of Industrial Engineering- - University of Salerno, Italy
* Corresponding author E-mail: riannone@unisa.it

Received 1 June 2013; Accepted 15 July 2013

DOI: 10.5772/56836

Abstract The integration among different companies functions, collaborative planning and the elaboration of focused distribution plans are critical to the success of each kind of company working in the complex *retail* sector. In this contest, the present work proposes the description of a model able to support coordinated strategic choices continually made by Supply Chain (SC) actors. The final objective is achievement of the full optimisation of Merchandise & Replenishment Planning phases, identifying the right replenishment quantities and periods.
To test the proposed model's effectiveness, it was applied to an important Italian fashion company in the complex field of fast-fashion, a sector in which promptness is a main competitive leverage and, therefore, the planning cannot exclude the time variable. The passage from a total push strategy, currently used by the company, to a push-pull one, suggested by the model, allowed us not only to estimate a reduction in goods quantities to purchase at the beginning of a sales period (with considerable economic savings), but also elaborate a focused replenishment plan that permits reduction and optimisation of departures from network warehouses to Points of Sale (POS).

Keywords Fashion Retail, Supply Chain Management, Merchandise and Replenishment Planning

1. Introduction

In markets with high-level competitiveness, companies can keep their competitive advantage only through re-modulation of company processes oriented to achieving greater flexibility and dynamism.

In this contest, the retail sector is difficult to manage because it is characterised by a rich number of stores or delivery points that big brands must manage. SCs are, in fact, complex because they are comprised of numerous actors; moreover, the competitiveness is high with little space for mistakes in stocks planning, goods replenishments or promptness of promotional campaigns. Mistakes and suboptimal choices will affect the entire chain, reducing effectiveness, efficiency and competitiveness. Changes in sales models, sector strengthening, globalisation and technology advances in recent years have blurred the boundaries between the traditional roles of manufacturer, wholesaler, distributor, seller and customer. In such a complex scenario, diligently planning activities cannot be overlooked. There are numerous software solutions for management of the entire Demand Planning process in the retail sector: they reflect the variety and variability of the sub-processes that comprise managerial activity at all function levels, from the forecasting to distribution to sales.

Based on these considerations, this current work proposes an innovative Demand Planning algorithm. From a logical point of view, the model incorporates the most effective characteristics of systems already developed (for example, historic data and deviation analysis) and introduces functionality and methodologies that are completely new, allowing us to overcome some critical aspects not yet solved. The model was applied to the case of a fashion retail company whose core business is the production of a specific group of products as well as the fulfilment of complete customer satisfaction, with all that it implies in productive, distributive and communication terms.

After an overview of the retail sector, with particular attention to issues of retail distribution and selling arrangements through a dense network of stores, and on fast-fashion, we will describe in detail the model and its application to the real case of an important Italian fashion company, owner of a well-known franchising brand situated all around the country. Following, after a first phase of customisation for introduction of the model to a particular business context, we will describe the strategical advantages that derive from its use and, in particular, the possibility of turning from the traditional push strategy of planning to take advantage of the more efficient pull strategy. To highlight the real effectiveness of the proposed model, we also present the process of validation and comparison between business planning results obtained with or without the proposed model.

1.1. *Fashion Retail*

The fashion retail industry registered a slow recovery in 2010, after hard knocks suffered in recent years due to the economic crisis. In particular, pre-sales data concerning turnover of 2010 indicates a growth of 6.5% over 2009, mainly driven by exports to emerging countries (Brazil, Russia, India, China, etc.) [1]. Over the last three years, Italian companies in this sector made dozens of acquisitions of other firms, both in Italy and the rest of the world. Today, in fact, the fashion industry is far from being insignificant in terms of economic size. Moreover, in this scenario, Italy occupies a place of prestige, together with France: Italian companies have, in fact, a turnover of 15 billion Euro on a worldwide total of 53 billion. The market share, then, is near to 30% and consists of both large companies producing luxury goods and of a multitude of medium and small enterprises [2].

In particular, changes have occurred in recent years in the competitive system, leading many companies to undertake initiatives to streamline operational processes, essentially aiming to improve the responsiveness to market demands, both in terms of adequacy of commercial proposals and product quality; all without neglecting, at the same time, the need to take steps to improve efficiency and speed of the entire Supply Chain [3].

The discussion often tends to focus only on finished products offered by the fashion system, but they are actually the result of a long, complex chain of phases and activities, and the success that the product has in the market depends greatly on their interactions. The term *Chain* means, literally, the route followed by the product in the production and distribution process, starting from its raw material and ending with the finished product available on the market. Furthermore, the chain includes coordination and integration activities between production and distribution stages. The actors involved are [4]:

- suppliers of materials and components;
- other actors that perform one phase of the supply chain, such as sub-contractors ("façonisti");
- third-party suppliers, that provide the company with clothes already sewn or semi-finished;
- Logistics providers;
- Points of Sale (POS).

In this sense, a fashion dress is much more than the creative effort of the designer. It is the result of using innovative fibres, woven with equipment specialised in fabrics, sewn in forms and colours that the fashion system proposes through fairs and specialised operators. Last but not least, distribution significantly contributes because it selects the offer and manages the demand through direct contact with the end consumer [2].

Compared to management of the typical variables concerning this business, increasingly critical to market success are monitoring the degree of consumer satisfaction with reference to the quality-price-styling mix of products commercialised, overseeing of distribution channels, development of effective and innovative communication strategies and, finally, the integration among the different Supply Chain's actors. In particular, for companies in the fashion system, time management (fabric procurement, production and delivery of finished items) has taken a crucial role in competitive comparison over the years. Between final demand, expressed by consumers who purchase clothing and accessories, and orders that distributors forward to producers, there are distorting effects (such as increases in volume and time shifts), that complicate the sales forecasting process more and more as it moves upstream in the manufacturing SC [5].

The *Pre-Season* stage of collection planning is far from the effective product sell and the planning activity covers a large time range. To this critical issue is added the presence of numerous articles in the collection that have different life-cycles or maturity degrees and positions with customers. Given these characteristics, it is necessary that a fashion product reach the consumer as soon as possible, before the product is *out of fashion*. In the past, in fact, the objectives of differentiation led to an uncontrolled expansion of variety, thereby neglecting production costs and times as well as the level of service offered the client. At present, however, even for the apparel sector, it is necessary to rationalise and accelerate the productive and logistic cycle, while respecting marketing needs. Essentially, a competitive advantage is no longer developed by classic actions taken to leverage on price or quality, instead it arises from experience matured in time management [3]. From the above-mentioned reasons, therefore, emerges the centrality of the operation's efficiency and managerial experiments aimed at further SC optimisation. The core business of fashion companies is no longer limited to the production of a specific product category but is realised in more complex customer satisfaction, all of which evolves from the production, distribution and communication point of view, because this is the only way of protecting a solid market share and profitable sales flow [2]. Even fashion companies should use, on one hand, forecasting techniques appropriate to the characteristics of all product-market segments and, on the other hand, Demand Planning and Sales Forecasting processes for monitoring performance indicators related to historic sales in past seasons or collections. In this way, companies can better calibrate parameters of statistical algorithms that periodically elaborate demand plans or undertake corrective management actions, that are aimed at increasing seasonal products' availability in POS, service level to customers and company's profitability and growth [5]. Studies in this field have shown the importance of information technology and communication when introducing innovative planning processes. Information technology, in fact, can help achieve a better, more efficient SC management, having a significant impact on production and on logistics, especially when they are headed by different subjects. Research has demonstrated how a product's visibility and transparency at each stage of the Supply Chain is crucial for fashion companies today and how it becomes even more significant if we consider actual trends that see many SCs affected by outsourcing and virtualisation in this sector [6].

In economic terms, given the complexity and importance of the fashion industry and, in particular, of fashion retailing, many studies have been conducted in this field over the years, starting from layout design [7] thorough organisation of production lines [8]. In particular, several researchers focused their attention on the connections and alliances between al the actors in the SC, from manufacturers to retailers. In 2010 Castelli and Brun [9] investigated on the alignment between retailers and manufacturers, examining several real-case studies in the Italian fashion industry. This study showed that pursuing retail channel alignment, by means of information exchange, communication tools and SC tools, can be a source of competitive advantage. In the same year, Swoboda et al. [10] analysed vertical alliances in the value chain both from the point of view of retailers and of manufacturers. The results showed a close relation between cooperation levels achieved in value chain activities and the degree of success in turnover, costs, and time-to-market.

Always in the contest of Supply Chain Optimisation, in 2013 Battista and Schiraldi [11] proposed a Logistic Maturity Model, used by a famous Italian firm of women's clothing as a guideline for increasing performance of the logistic process. Further, De Felice and Petrillo [12] proposed a multi-criteria methodological approach for evaluating performance of the fashion industry based on a balanced scorecard. In the same sector, several studies have been conducted on sales forecasting [13], using

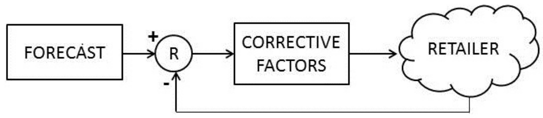

Figure 1. Model's General Work-flow for retail sector

neural networks [14] or an extreme learning machine [15] [16] or Fourier analysis [17]. In this context, in fact, a powerful sales forecasting system is essential to avoiding stock-out and maintaining a high inventory fill rate.

2. Model description

Figure 1 shows the work flow that constitutes the backbone of the entire model. A first *forecasting phase* returns a sales plan as output which is the aim of reference for all the activities down stream. For achievement of this objective, it is necessary to define some *Rules* (R) that allow you to act on the system by defining corrective factors: for example, they allow the definition of stock dimension according to the size or location of the point of sale. At the same time, retailers return a set of information (current data on sales, stocks, etc.) for comparison to initial forecasts. Any possible deviation requires intervention of corrective factors with an update of forecasts which is repeated recursively during the whole considered period.

The described work flow refers to a planning process that is divided into:

- **Merchandise planning**: Pre Season forecasting process, of medium-long term, aimed at the definition of commercial plans of purchasing and distribution of items to POS.
- **Replenishment planning**:In Season process, of short term, aimed at the definition of item's net requirements in stores, to replenish by sending consignment lots from logistic warehouses to the network.

Figure 2 shows the proposed model as a whole. The model consists of two macro blocks: the first, called *Pre Season*, accepts input of all historic data about sales of the closest ended time bucket and business data about products and forecasts for the period under review. This step provides as output the "Merchandise Plan" (MP) which contains all sales data expected to be achieved in the coming period (disaggregated by point of sale and product code). Each input factor, through well-defined computation rules, will have a different weight on the quantities defined by the MP. The second step of the model, called *In Season*, has the purpose of monitoring, in real time, actual sales results, to allow the "Replenishment Plan" (RP) elaboration, which are periodic supply plans recalibrated, work in progress, compared to initial estimates, to evaluate possible overestimation and underestimation resulting from the MP.

Before describing in detail the two phases that constitute the model, it is important to clarify the time horizons to which all before-mentioned plans refer (figure 3). Let us

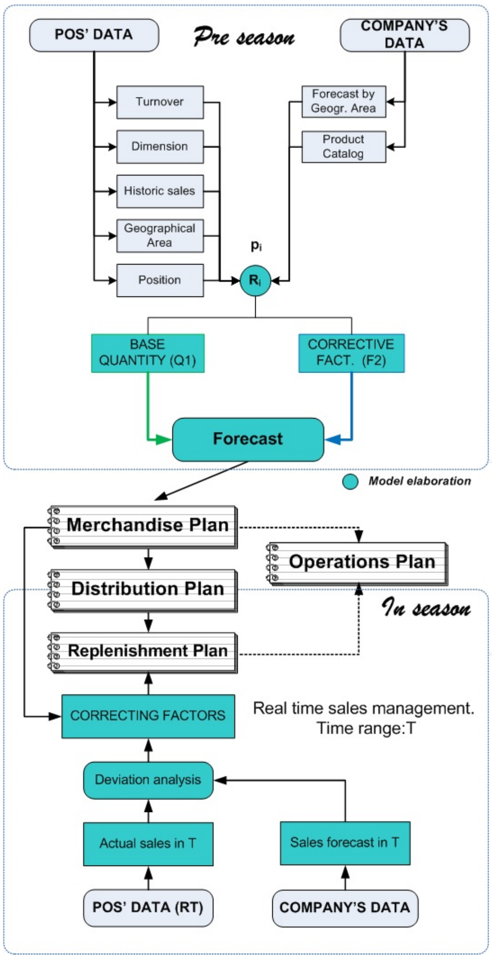

Figure 2. Model's Complete Work-flow

consider a generic *Time Bucket* (TB) for which we want to elaborate the different operational plans.

At the beginning of TB (i.e.: TB3) it is necessary to know the quantities to sell and distribute, so we must develop forecasts during the previous TB (i.e.: TB2). The model, then, uses data coming from the nearest closed TB, about which all definitive data are available, as input data for plan's elaboration. These data are processed by the model during the phase called *Pre Season*. Once all activities are planned, it will be necessary to control, during next period, that actual sales results are consistent with those expected. During *In Season* phases, then, the model activates an algorithm of monitoring and control, weekly or monthly repeated during the current period. Moreover, data during previous TB that are analysed for in season phases, for the rolling effect, will become input data for pre season planning of the following TB. This rolling effect of the forecasting analysis is repeated continuously.

2.1. Merchandise Plan

As already mentioned, *Pre Season* planning focuses on creation of the *Merchandise Plan*.

This is the plan which, at the beginning of period, records the results that we expect to achieve during the following sales period. Input data come from the POS and from other business functions in charge of preparing sales forecasts or product catalogues to launch into the market. In particular, data obtained from POS are:

- **turnover** data of the preceding period;
- **dimension** of both exhibition areas and internal warehouses. This information contributes to the definition of the maximum quantity of goods that the POS can receive;
- detailed data about **historic sales** in the preceding period: the user can choose to use either the absolute value of this quantity or other kinds of indicators (profit margin realised for each product category, ratio between sold and delivered quantities, etc.).
- the **geographical area** where the POS is placed allows for definition of the mix of products to send; the area can be expressed by indicating the province, the region or simply the area of the Country (North, South and Centre);
- the **position**, meant as the location of the POS for example in a suburb or town centre, allows you to better understand the referential consumer base.

To those first four inputs, are added those coming from other business functions, in particular:

- the product **catalogue**, developed by the design office, that indicates the number of items, product's categories, prices and brief descriptions.
- **sales forecasts** for each of the above-mentioned items, provided by the marketing managers.

All these inputs constitute the *parameters* on the basis of which the system generates the *rules* R_i for the computation of quantities. The different rules, and thus the upstream parameters, through an appropriate modulation of the switch a, can contribute to both the computation of *Base Quantities* (Q_B) of products to send to POS and the definition of the *Corrective Factors* (Q_C) used for the optimisation of the base quantities.
In particular, for base quantities, each rule suggests a value: to consider all the rules according to the importance given by the user, the value is multiplied by the corresponding weight and, finally, the model calculates the sum of all these products.

$$Q_B = \sum_{i=1}^{4} Q_i * p_i * a_i \qquad (1)$$

where:

Q_i: Base Quantity suggested by rule R_i
p_i: Weight attributed to rule R_i
a_i: choice coefficient (it is 1 if R_i is used for the computation of base quantity, otherwise is 0)

A mathematical algorithm takes in input base quantities and corrective factors and then computes, according to the criteria of the weighted average, sales forecasts (*forecast*),

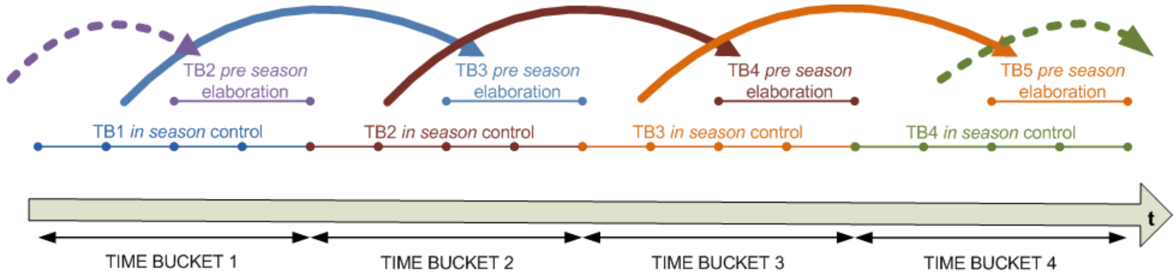

Figure 3. Time bucket and rolling effect of data used in the model during different time periods

	Rule	Value	p_i	a_i
Base Quantity	R_1	1	0.3	1
	R_2	3	0.7	1
Corrective Factor	R_3	+1	0.6	0
	R_4	+0.6	0.5	0

Table 1. Example of the computation of Q_B and Q_C for item 001

that are total product quantities the market can absorb during the whole sales period.

$$Q_C = Q_B * \sum_{i=1}^{4} F_i * p_i * (1 - a_i) \quad (2)$$

where F_i is the value of the corrective factor calculated with rule R_i.

Example. Let's assume that for the definition of the quantities we expect to sell for item 001 we make the choice reported in table 1.

The quantities of item 001 are computed as follows:

$$\begin{aligned} Q_B &= \sum_{i=1}^{4} Q_i * p_i * a_i = \\ &= (1 * 0.3 * 1) + (3 * 0.7 * 1) + (1 * 0.6 * 0) + \\ &\quad + (0.6 * 0.5 * 0) = 2.4 \end{aligned} \quad (3)$$

$$\begin{aligned} Q_C &= Q_B * \sum_{i=1}^{4} F_i * p_i * (1 - a_i) = \\ &= 2.4 * [(1 * 0.3 * 0) + (3 * 0.7 * 0) + (1 * 0.4 * 1) + \\ &\quad + (0.6 * 0.5 * 1)] = 2.16 \cong 2 \end{aligned} \quad (4)$$

The output of this first part is the *Merchandise Plan*, obtained by disaggregating sales forecasts and indicating the quantities for each POS that we expect to sell during the period considered.

2.2. Replenishment Plan

In common practice, suppliers deliver products to central warehouses in different moments within the time range considered. In the same way, goods are delivered to a POS in several phases as provided in the MP. In particular, at the beginning of the time bucket, only goods available at the moment in warehouse, are delivered. These goods are distributed to the POS according to the quantities defined in the *Pre Season* phase. The result is the first *Distribution Plan* (DP), that is the document issued by the Sales department to the Logistic function or to an external company, in cases where this function is outsourced. In its synthetic form, the DP includes data concerning quantities of each product code to be sent to the different POS.

We could also indicate, within this document, the delivery date and time, delivery lead time, the name of the POS responsible and other information useful to coordination amongst different logistic operators. At this point, it is necessary to perform a continuous monitoring of sales that may significantly differ from forecasts input to the system, both in excess and in defect. The continuous monitoring of sales helps the retail's *demand planner* recalibrate, work in progress, purchase orders to send to network logistic warehouses, for example increasing them in case of initial under forecast of quantities. Therefore, while as input in the first *Pre Season* phase we give annual sales forecasts, at this point we should limit the time horizon and consider only monthly forecast. This step is crucial for those products with a strong seasonality feature in their demand trend.

The model analyses the deviation between *actual* sales and *forecast* in the same period. The Δ or deviation is computed as follows:

$$\Delta = \frac{actual - forecast}{forecast} * 100 \quad (5)$$

Quantities are corrected (increased or reduced) of a value proportional to the error committed:

$$Q_c = Q_i * (1 + \Delta) \quad (6)$$

where: Q_C: corrected quantity during *In Season* phases;
Q_i: initial quantity obtained during *Pre Season* forecasting phase;
Δ: data deviation.

This operation is then repeated for each POS and each item. The document that we obtain is the RP, that is the POS' re-assortment plan issued once again to logistic and distribution function (figure 2). As mentioned, suppliers deliver ordered goods in two or more phases, thus stock that arrives in the network central warehouses from

TURNOVER RANGES			DIMENSION RANGES		
low	0	100 000	*small*	0	100
medium	100 000	300 000	*medium*	101	200
high	300 000	500 000	*large*	201	500

Table 2. Definition of turnover and dimension ranges

time to time will be delivered to POS according to the quantities established by this plan. If we choose the month as the time horizon for the control, then each month, the Replenishment Plan is updated and, with the same frequency, the POS are replenished.

3. Implementation of the model

3.1. Introduction

The design office is in charge of creating the collection to be launched on the market; starting from this and together with data about sales from the past season, sales forecasts are elaborated. Based on this information, purchase orders are developed to send to suppliers. Once goods are received into company warehouses, they are distributed to POS in several phases during the season. The company plans an average number of replenishments to evaluate logistic costs, but it often happens that POS make unexpected requests for small lots of sold-out goods. Further, deliveries from suppliers to the central warehouse are distributed over time.

The introduction of the model in the company ensures, instead, a higher reactivity during the entire Demand Planning process. Thanks to the analysis of information about both past and current seasons, it is possible to understand the limits and opportunities that the head office must face. In this way, the company can act in advance to balance demand and offer, optimising the level of service and stock through a continuous design in real time.

In brief, the objectives that the model will allow to achieve are essentially the following:

- **optimise distribution processes** to minimise SC crossing times;
- **develop focused replenishment plans** and projected onto future needs rather than the simple restoration of sold goods.

3.2. Merchandise Plan

3.2.1. Input Data

The first necessary phase, before going on with the model application to the business case, consists of particularising input voices described in the general case. In particular, turnover and dimension are defined through three ranges as indicated in table 2.

For each POS, in addition to city, turnover, dimension and location, it is necessary to enter data about historical sales (HS) of the previous season (equation 7).

% HISTORIC SALES		
very low	0%	40%
medium-low	41%	60%
low	61%	70%
high	71%	80%
medium-high	81%	90%
very high	91%	100%

Table 3. Definition of historical sales ranges

POSITION	GEOGRAPHICAL AREA
On The Street (SS)	North
Airport (ARP)	Centre
Shopping Center (SC)	South

Table 4. Division of POS for position and geographical area

$$HS = \frac{SQ}{DQ} \tag{7}$$

where SQ is the sold quantity and DQ is the delivered quantity.

The company identified as a target parameter a sales percentage equal to 85%, and then all distribution planning efforts at the beginning and during the season should be directed to achievement of this target. In particular, we considered this objective. Sales percentage should be indicated corresponding not only to each POS but also to each product category: this data entry operation is performed only once, at the beginning of the season. According to this definition, we choose to group POS into six different ranges as shown in table 7. The last two data concerning POS are to be considered with regard to position and geographical area (see table 4).

Referring to company related data, instead, the product catalogue considers the whole range of products that the company expects to commercialise during the considered season. It is clear that, in the fashion industry, the product mix in the catalogue, in their shapes, colours and fabrics, is different for each season. For the purposes of the model's implementation, we should clarify that at each product is connected to a unique code; however in this work and in accordance with business needs, they are grouped into families or product's categories. Each is assigned a code as shown in table 5.

We also introduced a higher level of detail that involves the grouping of these product's categories into three macro-families:

- *Clothing*: products that can be quickly purchased without the need to try them on in the dressing room, something that slows down the purchasing activity and requires that shopping assistants dedicate more time to customers.
- *Clothing to try on*: trousers, T-shirts, dresses, and all items that require the use of the dressing room, as well as a greater permanence of customers in the POS.
- *Accessories*: bags, scarves, jewellery, etc.

Cod.	Product's category
001	Woollen Cardigan
002	Cotton Cardigan
003	Jeans
004	Shawl
051	Coat
070	Scarf
007	Shoes
008	Dress
...	...

Table 5. Example of code's assignment

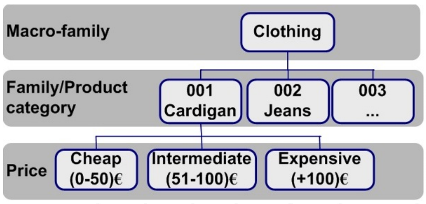

Figure 4. Level of information detail managed by the model

Researches carried out on past sales data demonstrated that, depending on the POS position (on the street, in airport, in shopping centres), customers show a different purchasing attitude towards these three macro-families. Finally, as regards the detail of information that, in this particular case, we chose to analyse, each product category is divided into three price ranges:

- *Cheap (C)*: from 0 to 50 Euro;
- *Intermediate (I)*: from 51 to 100 Euro:
- *Expensive (E)*: more than 100 Euro

Figure 4 shows an example of the structure of the product division into macro-families, categories and price ranges.

The choice of this level of information detail was primary dictated by the need for reliable forecasts.

The last parameter to be considered amongst inputs is forecast by geographical area. This parameter indicates sales estimates in different geographical areas for the whole season: it typically requires a collaboration between the Sales and the Design functions. The complexity of the fashion system and, as a consequence, of the business reality generates the presence of two nuclei together in the company: first, the creative one, oriented to the creation of a permanent stylistic identity, as well as the identification of seasonal stylistic themes and of consequent collections, and, second, the managerial one, which must be able to impose a brand identity on the market, through appropriate product strategies and a correct sales plan.

3.2.2. Elaboration of the model and definition of the rules

In a preliminary phase, in agreement with the company and with its management policies, we chose which factors to involve in the computation of the base quantity (Q_B)

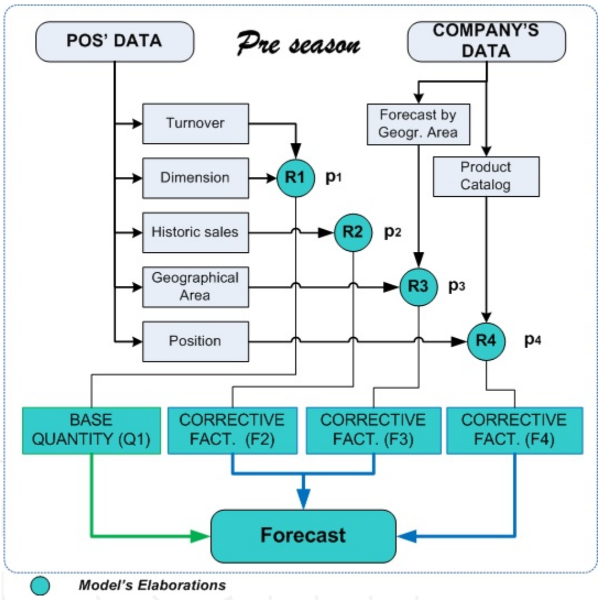

Figure 5. Model particularized for the business case

DIMENSION

small	*medium*	*large*	
1X	1X	2X	*low*
2X	2X	2X	*medium*
3X	3X	3X	*high*

TURNOVER

Table 6. Definition of Rule 1

and which to involve in the definition of the corrective factors (F_i) for the preparation of the MP. All other input parameters, with their own weights, will instead contribute to the definition of the remaining rules, useful to the computation of the corrective factors according to the scheme shown in figure 5. The rules, in accordance with the company's choices, were defined as shown in table 6.

The corrective factors were defined in a similar manner (table 7).

As the model shows, **Rule 1** depends on *turnover* and *dimension* and is expressed by the matrix in table 6.

For the definition of **Rule 2** (table 7) we must indicate, corresponding to the value of *historic sales*, the quantity to add or remove from the coefficient that indicates the base quantity as defined by Rule 1.

The initial analysis of the data coming from all the POS also highlighted that, based on the position, they register different sales for the three product's macro-families. *Accessories*, for example, are sold in greater quantities in airports because the purchasing activity is very quick; in shopping centres and on the street, they register very low success. A different trend is reserved for *Clothing to Try On*, while *Clothing* that does not need to be tried in the dressing room is sold in an equal percentage in all the POS.

Weight R2	0.7
% HISTORICAL SALES	**CORR. FACT.**
very low	-1
medium-low	-0.6
low	-0.3
high	0
medium-high	0.6
very high	1

Table 7. Definition of Rule 2

Weight R3 0.3

POSITION			
SC	*SS*	*ARP*	**MACRO-FAMILY**
-0.5	-0.5	1	*Accessories*
0.5	0,5	-0.5	*Clothing to Try On*
0	0	0	*Clothing*

Table 8. Definition of Rule 3

According to this trend, thanks to **Rule 3** (table 8) , base quantities are increased or decreased by the appropriate amount.

In the end, the company elaborated sales forecasts for each product category and for each geographical area: **Rule 4** (table 9) elaborates the different corrective factors in correspondence to each predictive input value. The basic idea is that, if we are supposed to sell 90% of dresses (cod.008), it is good to deliver to the POS a great quantity, even if its turnover and dimension are small and impose a coefficient 1X.

The last three rules, associated to the computation of the corrective factors, were assigned a weight p_i so that $(p_2 + p_3 + p_4 = 1)$, and that can vary during simulation phases. This choice should be made only once, when the model is introduced in the company, even if the parameters could change at any moment depending on needs.

3.2.3. Output Data

Ultimately, thanks to inputs that come from the sales network or other business functions, the model is able to elaborate an aggregate sales *forecast* concerning the whole season. In particular, for each product category and for the three different price ranges, the model calculates quantities that we are supposed to sell and that, therefore, we must purchase from the suppliers. This information is forwarded to producers in the form of Operation Plan; suppliers, from their point of view, know in detail the product category as well as the bill of material for each clothing item; thus they are able to elaborate the principal production plans starting from the forecast.

Disaggregating the quantities forecast, that is detailing them for each POS, we obtain the MP which, for operational needs, is divided into three groups:

- Accessories;
- Clothing;

Weight R4 0

% SALES FORECAST (CLOTHING)			
Subdept.	**North**	**Centre**	**South**
001	0.0	-0.6	-0.3
002	0.0	-0.6	-0.3
003	0.0	-0.6	-0.3
004	0.0	-0.6	-0.3
005	0.0	-0.6	-0.3
006	0.0	-0.6	-0.3
007	0.0	-0.6	-0.3
008	0.0	-0.6	-0.3
009	-0.6	1.0	-0.3
010	-0.6	1.0	-0.3
011	-0.6	1.0	-0.3
012	-0.6	1.0	-0.3
013	-0.6	1.0	-0.3
014	-0.6	1.0	-0.3
015	-0.6	1.0	-0.3
016	-0.6	1.0	-0.3
% SALES FORECAST (ACCESSORIES)			
112	-1.0	-1.0	-1.0
% SALES FORECAST (CLOTHING TO TRY ON)			
051	-0.6	-0.6	-1.0
052	-0.6	-0.6	-1.0
053	0.0	-1.0	-0.6
054	-0.6	-0.6	-1.0
055	-0.6	-0.6	-1.0
056	-0.6	0.0	0.6
057	-0.6	0.0	0.6
058	-0.6	0.0	0.6
059	-0.6	0.0	0.6
060	-0.6	0.0	0.6
061	-0.6	0.0	0.6
062	-0.6	0.0	0.6
063	-0.6	0.0	0.6
064	-0.6	-0.6	-0.3
065	-0.6	-0.6	-0.3
066	-0.6	-0.6	-0.3

Table 9. Definition of Rule 4

- Clothing to try on.

In addition to being a simple sales plan, it fully performs the functions of a Distribution Plan because it guides the company in the distribution planning during the first season's phases.

Table 10 shows an example of the MP.

For each family or product category (001, 002, etc.) and for each price range, the model calculates the appropriate coefficient for the definition of the quantities. Those corrected quantities (Q_r) are computed using the weighted average technique.

		008 Dresses			*009 Denim jacket*		
POS	$\boldsymbol{Q_B}$	**C**	**I**	**E**	**C**	**I**	**E**
1	2	2.8	2.6	0.0	2.6	1.6	0.0
2	3	3.6	3.6	0.0	3.3	3.6	0.0
3	2	2.3	2.6	0.0	1.9	2.6	0.0
4	2	1.6	2.3	0.0	2.3	2.3	0.0
5	2	2.3	2.6	0.0	1.9	2.6	0.0
6	1	1.6	1.6	0.0	0.9	1.6	0.0
7	2	2.6	2.6	0.0	1.9	2.6	0.0
8	1	1.3	1.3	0.0	0.4	1.3	0.0
9	2	2.3	2.6	0.0	1.9	2.6	0.0
10	2	2.6	2.6	0.0	2.3	2.6	0.0

Table 10. MP's Structure

ACCESSORIES

code	112			113		
Price Range	C	I	E	C	I	E
% Sales Forecast	42%	36%	0%	8%	0%	0%

CLOTHING TO TRY ON

code	089			090		
Price Range	C	I	E	C	I	E
% Sales Forecast	0%	23%	11%	0%	32%	0%

CLOTHING

code	001			002		
Price Range	C	I	E	C	I	E
% Sales Forecast	0%	0%	0%	0%	0%	0%

Table 11. Input scheme of the forecasts in season

$$Q_r = Q_B * \sum_{i=3}^{4} F_i * p_i \tag{8}$$

3.3. Replenishment Plan

To define the RP, for each POS and for each product category, it is necessary to enter into the model, once again, the sales percentage. The objective is to perform an immediate check on the sales trends on the basis of deciding how to replenish the store. Remember that in this business case these data are easily traceable from the database *extractions*.

The second input factor is the *sales forecast* processed with the same level of detail as the previous data and referring to the time period considered. So again the Sales and the Design functions jointly study the market, the current trends or the occurrence of particular events (offers, fashion week, etc.) and elaborate forecasts that ignore the historical factor.

Input data are elaborated by the model that gives as output the RP, itself divided into: Accessories, Clothing, Clothing to Try On.

	$\boldsymbol{\Delta_2 > 0}$	$\boldsymbol{\Delta_2 < 0}$
$\boldsymbol{\Delta_1 < 0}$	$Q_C = Q_B * (1 + \Delta_1)$	$Q_C = Q_i$
$\boldsymbol{\Delta_1 > 0}$	$Q_C = Q_B$	$Q_B = Q_B * (1 + \Delta_1)$

Table 12. Deviations

This plan is similar to the MP already shown, except for the base quantities that are no longer reported. It is clear, however, that the algorithm for the computation of the quantity coefficient is not based on the weighted average technique anymore but rather on the deviation analysis. In particular, for each product category and for each price range, we analyse the deviation between the *actual* sales and the sales *forecast* in the same time period and for each POS. The Δ_1 (deviation) is computed through the equation 10.

$$\Delta_1 = \frac{actual - forecast}{forecast} * 100 \tag{9}$$

The algorithm also computes a second deviation (Δ_2) between the sales of each POS and the average sales of the company:

$$\Delta_2 = \%CompanySales - \%PSSales \tag{10}$$

In this way, we consider both the hypothetical forecast error and the company target of maximising and standardising the sales percentage in all the POS. In general, because the Δ can be greater or less than zero, in this case we can identify four different scenarios for which we should define an action plan and formulate the new distribution plans.

The quantities to be distributed to the POS, calculated at the beginning of the season (Q_B), if necessary, are corrected (increased or decreased) in a value proportional to the error we make, thus obtaining a new quantity (Q_C: corrected quantity) with which to replenish the POS in the current season. The possible scenarios are the following (table 12):

- $\Delta_1 < 0$: the product is sold less than expected, therefore we must decide whether to decrease the initial quantity or to leave it unchanged:
  - Δ_2 <0: the POS sells more than the company average, the quantity is not changed:

    $$Q_C = Q_B$$

  - Δ_2 >0: the POS not only sells less than what we expected but also less than the company average, then we decrease the quantity:

    $$Q_C = Q_B * (1 + \Delta_1)$$

- Δ_1 >0: the product is sold more than what we expected, then we must decide whether to increase the initial quantity or to leave it unchanged

- Δ_2 <0: not only the POS sells more than what we expected but also more than the company average, then we increase the quantity:

$$Q_C = Q_B * (1 + \Delta_1)$$

- Δ_2 >0: the POS sells less than the company average, then the initial quantity is not changed :

$$Q_C = Q_B$$

The RP is the POS reassortment plan issued by the logistic and distribution function. This plan is obtained by correcting the initial MP according to the results of the deviation analysis.

In addition, it is possible to activate, corresponding to the POS' dimension, a threshold that indicates the maximum goods quantity that a store can contain. The aim is to prevent small POS from receiving, during the reassortment, more product than what they can actually hold.

4. Validation and analysis of the results

The last step of the process, the validation, consists of verifying that the model is:

- sufficiently accurate for the applications of interest;
- able to reproduce and manage a real system and its limits.

In particular, this validation phase consists of a comparison between the behaviour of the system governed by the current strategies (push) and the one governed by the strategies suggested by the model (push-pull). This comparison was performed thanks to a simulation tool developed with *Arena Simulation Software®*.

The simulator accepts as input a dataset, that is composed by the demand and deliveries profiles built on the basis of past data, given as output the POS' demand and stocks day by day. Figure 6 shows the simulation process performed for the planning of the season Spring/Summer 2 (S/S 2) starting from the previous, S/S 1. In particular, the time range under examination is the one that goes from Week 12 to Week 34, from which we are interested in knowing sales data for five products, found to be representative of the entire collection:

1. bags (Accessories);
2. t-shirts (Clothing to Try On);
3. dresses (Clothing to Try On);
4. shawls (Clothing);
5. jackets (Clothing).

The simulator, as mentioned, processes the values of demand and daily stock and starting from them, it is necessary to go back to the sold quantities. Therefore, after having merged data on a weekly basis, the sold quantities until week s (QV_s) are computed as follows:

- if the stock, at week s, i positive ($G_s > 0$) then

$$QV_s = \sum_{i=1}^{s} C_i - G_s$$

- if the stock, at week s, is negative ($G_s < 0$) then it means that the POS sold more than was available during Week $s-1$, while during Week s, the stock is actually null, so:

$$QV_s = QV_{(s-1)} + G_{(s-1)}$$

In figure 6 the *demand profile* corresponds to the demand accurately registered every week of the season S/S 1; in the same way the *delivery profile* was built using real delivery data of the same reference period.

The simulator accepts as input these profiles and simulates the behaviour of the entire season in terms of POS demand and stock. Data we obtained are considered *historical sales data* and are used as inputs in the model, which is then able to develop the MP for season S/S 2 that guides deliveries only of the goods available at the beginning of the period.At this point, it starts the simulation of the *in season* periods of season S/S 2 that, from time to time, are analysed by the model for the periodic elaboration of optimised distribution and replenishment plans. Using as input data the same historical demand profile and the deliveries suggested by the model for the first week, we start a new simulation that generates the sales quantities for the first month (Week 12-15); the model checks data referred to in this period and generates a first RP which suggests deliveries to be made during Week 16. In the end, delivery profile 2 is updated by inserting a new record corresponding to Week 16. We repeat cyclically what we did in the previous step, in other words the simulator generates the results for the second month of the season 2 (Week 16-19) starting from which the model can elaborate the second RP for Week 20. This process of simulation and elaboration of the replenishment plans continues until we cover all weeks of the season. In this case, at the beginning we decided to make one delivery a month; however it is possible to distribute goods once every 15 days, thus controlling sold quantities not at the fourth week but once every two weeks.

It is now possible to compare the actual results achieved during season S/S 2 and those that we would obtain if, being equal the market demand, the company had used the model. In particular, the simulator generated a dataset for a store with a medium dimension and turnover , chosen as representative of the company network. The first diagram in figure 7 shows the percentage of sold quantity over delivered one recorded every week: blue lines always reach a greater height than the red ones, reflecting the fact that the quantity of goods the model suggests to deliver are in line with real requirements. In fact, observing the second diagram, the value of the stock obtained using the actual strategy is always higher than the one provided by the model, then bearing both capital costs for stocks and costs for the withdrawal of unsold goods at the end of the season.

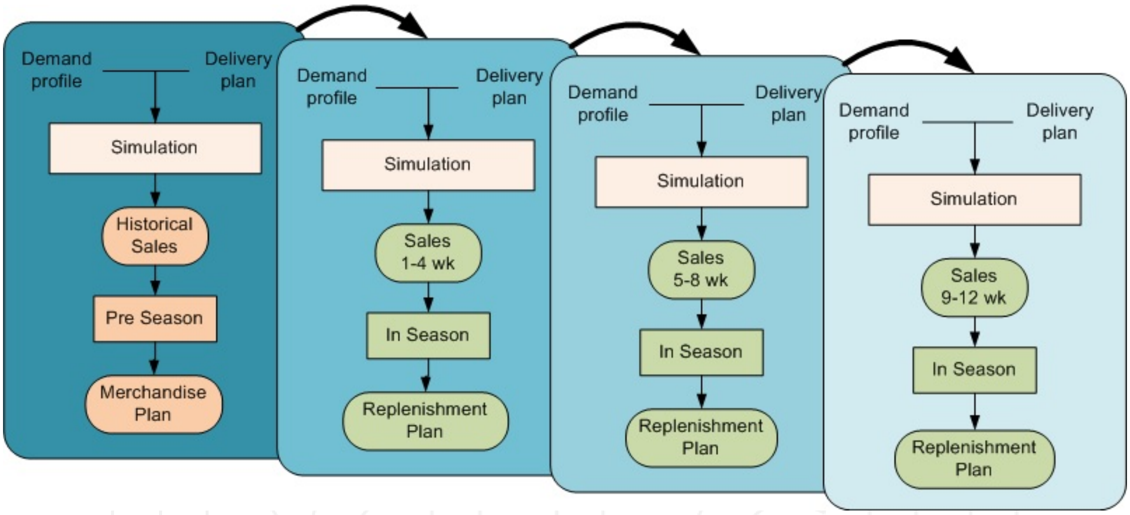

Figure 6. Reproduction of information and material flow with Arena Simulation

Figure 7. Advantages of the model in terms of stock and % of sold quantities

	001		002		003		004	005	
	C	I	C	I	I	E	C	I	E
Curr.	77%	82%	87%	76%	96%	77%	56%	52%	57%
Mod.	91%	78%	100%	100%	100%	100%	78%	81%	80%

Table 13. Advantages of the model in terms of stock

As a consequence, the model is able to achieve the business target of a percentage of sold quantities equal to 80% and quite uniform for all items (see table 13). Thanks to an optimised allocation of the goods, we are able to make available on shelves the right quantities of the right products.

At the end of the season the delivery plan computed by the model is better distributed over the time, in stark contrast to the chaos that currently governs consignments from the central warehouse to POS. The main problem is that today the company is unable to react quickly to sudden demands of customers for unavailable goods. On many occasions the company reacts with ad hoc shipments of single items or by moving product from one store to another (these episodes are witnessed by the red spheres of smaller dimensions in figure 8).

The inventory turnover(I_T)is, instead, a key parameter for the evaluation of the company's logistic management (equation 11).

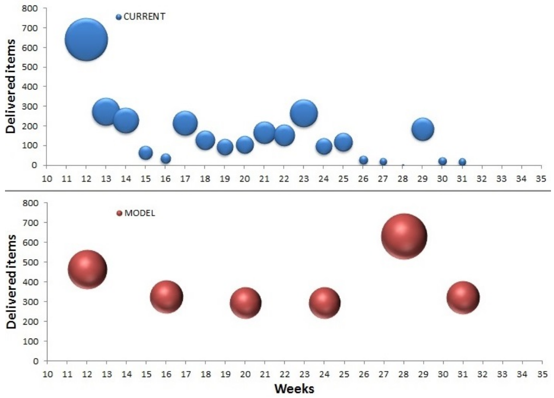

Figure 8. Deliveries during season S/S 2

	001			002		003		004	005		
	C	**I**	**E**	**C**	**I**	**I**	**E**	**C**	**I**	**E**	**Avg**
Curr.	2.07	1.82	1.77	1.96	2.01	2.32	1.50	0.93	0.87	1.00	**1.62**
Mod.	7.43	1.86	12.78	5.70	9.47	4.91	4.26	2.02	3.33	2.32	**5.41**

Table 14. Inventory turnover

$$I_T = \frac{M_O}{G_M} \tag{11}$$

where M_O and G_M are delivered material and mean level of stocks, respectively.

Table 14 shows that, at present, the company records rather low values for this index, which means that the resources invested for purchasing goods have been immobilised for a long period, giving rise to financial problems. On the contrary, the model, following real market demands, records much higher inventory turnover values, ensuring a fast return on investment. For example, stocks of cheap bags (code 001 Cheap) were renewed seven times during season, against the only two times recorded without use of the model for planning.

Assuming, instead, that in season S/S 2, a demand profile (blue in figure 9) was different from the one in season S/S 1 (in red), the model effectively appears to be very reactive and, in fact, in Week 20 suggests delivery of more goods to compensate for the increase of sales.

At this point, it is worth highlighting one of the limitations of the model in these conditions: the level of service. Today, this index always reaches values equal to 100% because the company delivers to POS more products than necessary, as shown in the first diagrams. Table 15 shows, instead, values of the level of service obtained using the model: cells with the string *no* indicate, for that particular week, that there were no requests for the product in the column; underlined there are cases in which we registered a low level of service, resulting in lost sales. Especially during the last weeks of a season, after having reached the peak of sales, by using the model we risk having no more items to sell because of the search of a minimum level of stock.

We should, however, point out that, to make analysed data more respondent to reality, demand profiles were constructed considering real sales of past seasons and the demand is, therefore, referring to what was available to sell in the store. However, we do not consider the possibility of selling other products that our analysis suggests are highly required in one POS more than another (for example in airports more than in shopping centres). In other words, we should consider that the customers' purchasing behaviour is different if they can choose among several items: then, against a lower level of service at the end of the season, we should consider an hypothetical increase in profitability ensured by the model.

To test the utility of the model, in addition to the simulator, we also used a less complex and more immediate technique to underline the advantages in economic terms for the purchases at the beginning of the season.

We entered as input to the model sales data of season S/S 2011 and the model returned as output the quantities to be delivered to POS in the following season, that is S/S 2012. In particular we found that, the purchased items for season 2012, were too many, resulting in a high inventory level in the POS. If we had used the model, the company would have had access to a purchasing plan computed on the basis of data of the year 2012 and, thereby, much closer to real sales results. Figure 10 shows the quantities actually purchased by the company and the ones that the model, if used for the same season, would suggest.

5. Conclusions

The main advantage offered by this model is to consider each POS as an independent reality which serves a clientèle with different behaviours and characteristics. Each POS receives a suitable product mix, chosen principally by considering what was sold in the previous season and the socio-economic characteristics that influence purchasing behaviour, as well as several other parameters chosen by the user: the company is, then, sure to deliver the right product to the right place at the right moment. This reduces the risks associated to the forecast reliability which are translated in stock-outs or overstocks. In particular, this significantly reduces the probability of occurrence of the two following errors, characteristic of a bad demand forecast:

- *Under-forecast* of the final demand: it results in the reduction of the level of service guaranteed to customers, because of the unavailability of the required product (stock-out), the need to increase product stocks at the intermediate storages of the logistic/distribution network (safety stock), the need to issue urgent production and distribution orders (altering the structure of the optimised plan previously formulated), or the loss of image for the company (detected as unreliable and not precise in the deliveries to customers);
- *Over-forecast* of the final demand: it results in excessive stock levels and connected management and

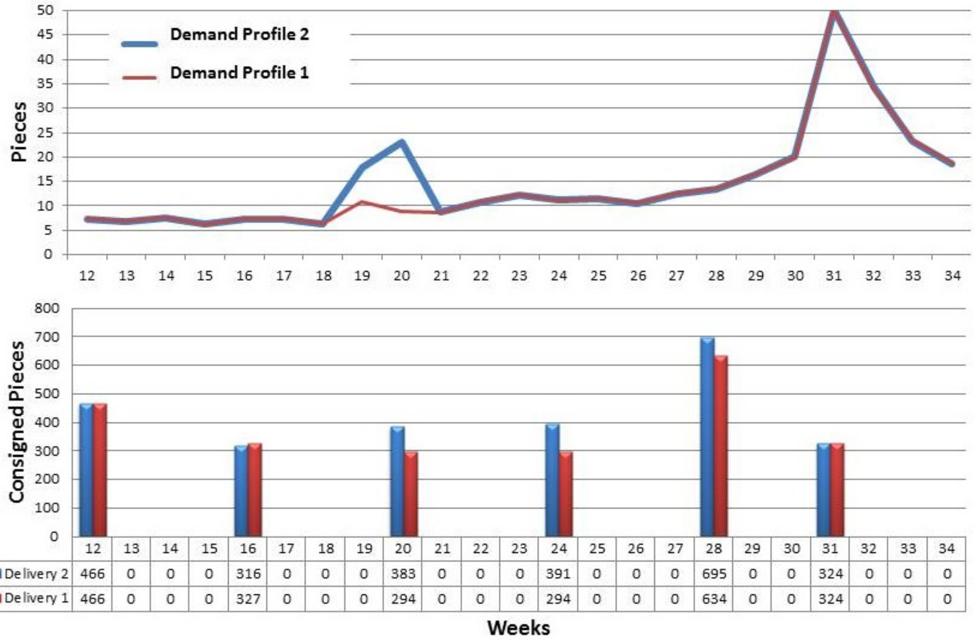

Figure 9. Sudden increase of demand

	001			002		003		004		005
Week	**C**	**I**	**E**	**C**	**I**	**I**	**E**	**C**	**I**	**E**
12	100%	100%	no	100%	100%	100%	no	no	100%	100%
13	100%	100%	no	100%	100%	no	no	no	100%	100%
14	100%	100%	no	100%	100%	100%	no	100%	100%	100%
15	100%	no	no	100%	100%	100%	no	75%	no	100%
16	100%	no	no	100%	100%	100%	100%	no	no	no
17	100%	100%	no	100%	100%	no	100%	no	no	100%
18	100%	100%	no	100%	100%	100%	100%	no	no	no
19	100%	100%	0%	100%	100%	100%	100%	47%	no	100%
20	100%	100%	0%	100%	100%	100%	100%	56%	no	100%
21	100%	no	0%	100%	100%	100%	100%	no	no	100%
22	100%	100%	no	100%	100%	100%	100%	no	no	98%
23	100%	100%	no	100%	100%	100%	100%	52%	no	89%
24	100%	no	no	100%	100%	100%	100%	no	no	100%
25	100%	100%	no	100%	100%	100%	100%	53%	100%	100%
26	100%	100%	no	100%	100%	100%	100%	no	no	no
27	100%	no	no	100%	100%	100%	100%	no	no	no
28	100%	100%	no	100%	100%	100%	100%	no	no	100%
29	100%	100%	no	100%	100%	100%	100%	no	no	100%
30	100%	100%	no	100%	100%	100%	100%	59%	no	100%
31	100%	100%	no	100%	100%	100%	100%	55%	100%	100%
32	100%	100%	no	100%	100%	100%	100%	52%	100%	100%
33	100%	100%	43%	100%	100%	98%	94%	no	100%	98%
34	100%	100%	no	98%	100%	92%	91%	50%	100%	92%

Table 15. Level of service

holding costs for the products at the warehouses (both central and internal to POS), excessive and incorrect allocation of the production capacity, risk of physical deterioration or technological obsolescence of products.

Thus, thanks to an optimised product allocation, we reduce several cost items connected specifically to logistics and to stocks at the end of the period. In season planning, in fact, guarantees the minimum transport cost for the replenishment of stores and the delivery of products to

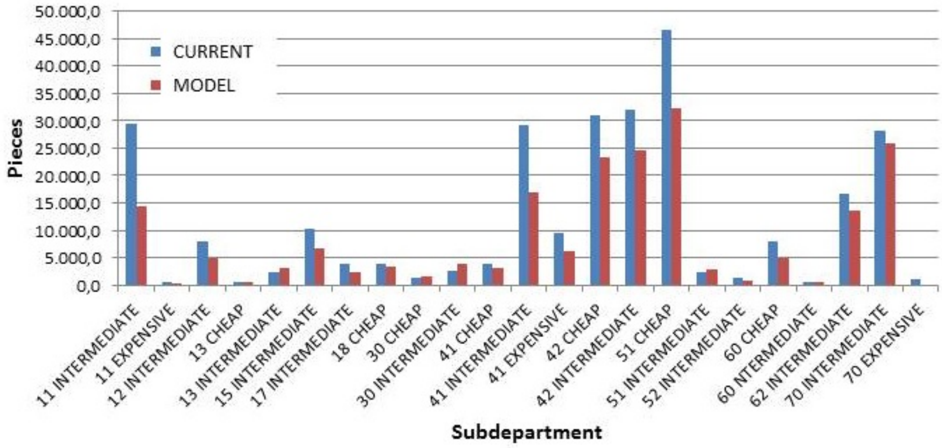

Figure 10. Difference between the actually purchased quantities for S/S 2012 and the ones computed by the model for clothes to try on

each POS with a grater chance of sale. Furthermore, the model is designed and developed to ensure a perfect integration between the different SC actors within such a complex sector as the retail one. In this sense, the model helps different planners to intervene in an intelligent way on the wide dataset held by the companies. In fact, it is a real solution of Business Intelligence (BI), contributing to the profitability and to the business development with all the characteristics discussed in this paper. In particular, the model, as a BI tool, is able to optimise the performances of the core company's processes, contributing to reduction of costs and increase of revenue. Concerning cost reduction, the main advantages are achieved thanks to performance control, monitoring of key performance indicators (KPI) and, last but not least, to optimisation of the SC.

6. References

[1] Osservatorio ICT and business innovation, editors. *ICT nel fashion retail quali evoluzioni in un contesto globale?* School of Management-POLIMI-Dipartimento di Ingegneria Gestionale, 2011.

[2] Silvio Modina. *Il negozio di moda: strategia, valutazione e gestione economico-finanziaria*. Franco Angeli, 2012.

[3] Alessadro Coraggia. La supply chain management come strumento di marketing. il caso inditex-zara. Master's thesis, Universitá Luiss Guido Carli, 2009.

[4] S. Saviolo; S. Testa. *Le imprese del Sistema moda. Il management al servizio della creativitá*. ETAS LIBRI, 2005.

[5] Damiano Milanato; Fabrizio Dallari. Metodologie di sales forecasting nel fashion retail. *Logistica*, page 28, Settembre 2011.

[6] ICT4 Executive. L'ict nel fashion retail, una leva per il successo, 2011.

[7] F. De Carlo; M. A. Arleo; M. Tucci; O. Borgia. Layout design for a low capacity manufacturing line: a case study. *International Journal of Engineering Business Management*, 2013.

[8] F. De Carlo; M. Tucci; O. Borgia. Bucket brigades to increase productivity in a luxury assembly line. *International Journal of Engineering Business Management*, 2013.

[9] Cecilia Maria Castelli; Alessandro Brun. An empirical study of italian fashion retailers. *International Journal of Retail & Distribution Management*, 38(1):22–24, 2010.

[10] Bernhard Swoboda; Nicolae Al. Pop; Dan Cristian Dabija. Vertical alliances between retail and manufacturer companies in the fashion industry. *Amfiteatru Economic*, XII(28):634–649, 2010.

[11] Claudia Battista; Massimiliano M. Schiraldi. The logistic maturity model: Application to a fashion company. *International Journal of Engineering Business Management*, 2013.

[12] Fabio De Felice; Antonella Petrillo; Claudio Autorino. Key success factors for organizational innovation in the fashion industry. *International Journal of Engineering Business Management*, 2013.

[13] Maria Elena Nenni; Luca Giustiniano; Luca Pirolo. Demand forecasting in the fashion industry: a review. *International Journal of Engineering Business Management*, 2013.

[14] Kin-Fan Au; Tsan-Ming Choi; Yong Yu. Fashion retail forecasting by evolutionary neural networks. *Internationl Journal of production Economics*, 114:615–630, 2008.

[15] Min Xia; Yingchao Zhang; Liguo Wenga; Xiaoling Ye. Fashion retailing forecasting based on extreme learning machine with adaptive metrics of inputs. *Knowledge Based Systems*, 2012.

[16] Zhan-Li Sun; Tsan-Ming Choi; Kin-Fan Au; Yong Yu. Sales forecasting using extreme learning machine with applications in fashion retailing. *Decision Support Systems*, 46:411–419, 2008.

[17] Andrea Fumi; Arianna Pepe; Laura Scarabotti; Massimiliano M. Schiraldi. Fourier analysis for demand forecasting in fashion company. *International Journal of Engineering Business Management*, 2013.